

REMARKS

STATUS OF THE CLAIMS

Claims 18-21, 23-25, 27-29, and 41-66 remain in the case. Claims 18-21, 23-25, and 27-29 stand rejected. Claims 18 and 25 have been amended. Claims 41-66 have been added. No new matter has been added. Claims 1-17, 22, 26, and 30-40 have been cancelled. Applicants respectfully traverse the rejections of Claims 18-21, 23-25, and 27-29. New Claims 41-66 substantially encompass the subject matter of previously cancelled Claims 1-17 and 30-40, updated to reflect the amendments to Claims 18 and 25. The amendments are supported in paragraphs [0011]-[0013], [0049]-[0064], [0071], [0075]-[0077], [0094-0095], [0104], [0109], [0112], and [0114].

RESPONSE TO CLAIM REJECTIONS UNDER 35 U.S.C. § 103(a)

Claims 18-25, and 27-40 stand rejected under 35 U.S.C. §103(a) as being unpatentable over “Application of Fuzzy Logic to Reliability Engineering” (hereinafter *Bowles*), in view of “Improved Disk Drive Failure Warnings” (hereinafter *Hughes*), “Fuzzy Rule-based Expert System for Power System Fault Diagnosis” (hereinafter *Monsef*), U.S. Patent No. 5,832,467 to Wavish (hereinafter *Wavish*), “Fixed Time Life Tests Based on Fuzzy Life Characteristics” (hereinafter *Kanagawa*), “Fuzzy Fundamentals” (hereinafter *Cox*), “Fuzzy Guidance Controller for an Autonomous Boat” (hereinafter *Vaneck*), and/or “A Layer Based Computational Model Plus a Database Structure as a Framework to Build Parallel Fuzzy Controllers” (hereinafter *Andrade*).

Graham v. John Deere Co., 383 US 1, 148 USPQ 459 (1966) sets forth the factual inquiry necessary to determine obviousness. To make a *prima facie* case of obviousness, one must: determine the scope and contents of the prior art; determine the differences between the prior art and the claims at issue; resolve the level of ordinary skill in the pertinent art; and consider objective evidence present in the application indicative of obviousness or nonobviousness.

Applicants respectfully assert that the claims at issue are not obvious. First, not all elements of the amended claims are taught or suggested in the art of record, and second, the art of

record comes from vastly different fields than does the Applicants' claimed invention and is clearly nonanalogous art. Applicants respectfully submit that *Bowles, Hughes, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade* do not teach assisting a user in generating a failure prediction algorithm comprising fuzzy logic rules, generating machine-readable code from the stored failure prediction algorithm, testing the machine-readable code with sample data to produce a result, or selectively revising the failure prediction algorithm such that the result corresponds to an expected result.. Applicants further submit that *Bowles, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade* are nonanalogous art, and that these differences between the prior art and the claims at issue render the claims at issue nonobvious and allowable under 35 U.S.C. § 103(a).

To highlight the differences between the present invention and the cited prior art, as mandated by *Graham*, a summary of the claimed invention and of the prior art may be useful. Generally, the claimed invention seeks to overcome problems of the prior art associated with the maintenance and storage of data within a storage system and with the development of failure prediction software for the storage system. (*Specification*, ¶ [0001]). For example, in the art, complicated software routines written by experienced software engineers use a high number of input variables to provide stability reports for storage systems. This means that the algorithms are determined by software engineers and not by end-users that are most familiar with storage systems, and that the algorithms are not customizable to unique circumstances. End-users are stuck with whatever algorithm the software engineers have established, and must wait through a lengthy development cycle for updates, with no guarantee that a future release will bring any changes. Additionally, conventional software uses discrete threshold values which often do not adequately reflect the range of operating conditions in which storage systems operate, generating costly false-positives.

Independent Claim 18, as amended, specifically requires “assisting an **end-user of a storage system** in generating a failure prediction algorithm **for the storage system**, the failure prediction algorithm comprising **fuzzy logic rules**, the failure prediction algorithm stored in a **natural language format**; generating machine-readable code from the stored failure prediction algorithm **in response to input from an end-user**, the machine-readable code configured to

execute on the storage system; testing the machine-readable code with sample data to produce a result **in response to input from an end-user;** and selectively revising the failure prediction algorithm **in response to input from an end-user** such that the result corresponds to an expected result.” (emphasis added).

Independent Claim 25, as amended, specifically requires “gathering performance data **for a storage system;** executing a failure prediction algorithm on the performance data to produce a result, the failure prediction algorithm comprising **fuzzy logic rules generated by an end-user of the storage system,** the fuzzy logic rules defined by **conditional statements that include subjects, adjectives, and verbs familiar to personnel in the storage system field;** tuning the failure prediction algorithm by **adjusting a fuzzy variable definition** in response to **input from an end user of the storage system;** and selectively **forecasting failure** of one or more components of the storage system in response to the result.” (emphasis added).

New independent Claim 41 is an apparatus for developing failure prediction software for a storage system that comprises an editor, a code generator, a test module, and a revision module. New independent Claim 47 is an apparatus for predicting component failure within a storage system comprising a performance monitor, a processor, a determination module, and an interface. New independent Claim 52 is a system for predicting component failure within a storage system comprising a controller, a communication module, a drive mechanism, and an analysis module. New independent Claim 56 is an apparatus for developing failure prediction software for a storage system. New independent Claim 62 is an article of manufacture comprising a program storage medium readable by a processor and embodying one or more instructions executable by a processor to perform a method for developing failure prediction software for a storage system.

Summary of *Bowles*

Bowles describes several models for characterizing system reliability using fuzzy arithmetic. (*Bowles*, Abstract). *Bowles* uses general examples, such as “Hans ate v eggs for breakfast,” focusing on the mechanics of fuzzy arithmetic instead of specific applications. (*Bowles*, pg. 438, ¶ 5). Two specific areas of art mentioned in *Bowles* are the nuclear and aerospace industries. (*Bowles*, pg. 442, ¶ 6).

Bowles does not address failure prediction algorithms or storage systems, addressing instead general system reliability and the general probability of events. (*Bowles*, Abstract; *Bowles*, pg. 439, col. 2). *Bowles* further does not teach a method for assisting an end-user in generating a failure prediction algorithm comprising fuzzy logic rules, as required by the claims at issue, not mentioning an end-user, a storage system, or a failure prediction algorithm.

Summary of *Hughes*

Hughes proposes various algorithms for SMART failure prediction systems to predict failure in disk-drives. (*Hughes*, Abstract). The algorithms proposed in *Hughes* are designed to be run on as microprocessor firmware on a disk-drive. (*Hughes*, Abstract).

The Office Action suggests that “running the ‘SMART’ application of *Hughes*” is equivalent to generating machine-readable code from the stored failure prediction algorithm in response to user input as required by Claim 18. (Office Action, Page 4, ¶ 1).

Applicants respectfully submit that running an application is not equivalent to “generating machine-readable code from the stored failure prediction algorithm” of Claim 18. The microprocessor of *Hughes* does run the SMART failure warning algorithm, which presumably comprises machine-readable code. This does not necessarily imply that the SMART failure warning algorithm was compiled, as device level microprocessor code is often written directly as machine readable code and not compiled. Even if it was compiled, *Hughes* does not teach compiling a failure prediction algorithm comprising fuzzy logic rules stored in a natural language format into machine readable code.

In direct contrast to the claims at issue, *Hughes* teaches that a storage drive itself measures up to 30 failure attributes, and that this technology is “manufacturer proprietary.” (*Hughes*, pg. 351, C1:20-43). Because the technology is proprietary, *Hughes* does not teach what, if anything is compiled, and clearly does not teach generating machine-readable code from a natural language format failure prediction algorithm comprising fuzzy logic rules. It is more likely that the SMART algorithm is implemented as a combination of hardware sensors and low level instructions, however *Hughes* expressly states that the implementation of the technology is proprietary, and is thus unknown. *Hughes* cannot teach something that is unknown. *Hughes*

does not teach, suggest, or even mention compiling, and clearly does not teach generating machine-readable code from a stored failure prediction algorithm in a natural language format.

Additionally, because the technology is proprietary, *Hughes* clearly does not teach that end-users of a storage system may generate a failure prediction algorithm for the storage system. By teaching that failure attributes should be manufacturer proprietary, *Hughes* directly teaches away from the claimed invention as amended. *Hughes* teaches the solutions already available in the art as described above, depending on experienced software engineers and their development cycles to define “manufacturer proprietary” warning algorithms.

Summary of *Monsef*

Monsef demonstrates a component oriented fuzzy expert system for power system fault diagnosis. (*Monsef*, Abstract). *Monsef* teaches the diagnosis of existing faults in a power system by modeling the power system and comparing simulation results with actual system information to diagnose a power system fault. (*Monsef*, pg. 186, ¶ 4).

Monsef does not teach testing machine-readable code with sample data to produce a result in response to end-user input, as required by the claims at issue. Applicants respectfully submit that modeling a power system and running a simulation to diagnose an existing power system fault does not read on testing a machine-readable code failure prediction algorithm with sample data to produce a result in response to user input. *Monsef* does not teach machine-readable code, a failure prediction algorithm, or sample data.

Summary of *Wavish*

Wavish teaches a rule-based data processing apparatus for optimization of behavioral prediction in Real Time ABLE (RTA) autonomous agents such as robots, artificial intelligences, and the like. (*Wavish*, col. 1, ll. 4-67). *Wavish* teaches the use of genetic algorithms that generate chromosomal representations. (*Wavish*, Abstract; *Wavish*, col. 2, ll. 47-51).

Wavish teaches that autonomous agents are defined by a first set of rules and a second set of rules. (*Wavish*, col. 2, ll. 5-26) The second set of rules predicts the agent state changes caused

by the first rules. (*Id.*). The autonomous agent monitors the accuracy of the second set of rules and modifies the second set of rules to increase their accuracy. (*Id.*).

The autonomous rule modification of *Wavish* does not read on selectively revising a failure prediction algorithm in response to end-user input such that the result corresponds to an expected result for several reasons. *Wavish* does not teach revising a failure prediction algorithm, but instead teaches modifying behavioral rules. Additionally, even if *Wavish* did teach revising a failure prediction algorithm, *Wavish* teaches that the autonomous agent modifies the rules itself, in response to its' own monitoring of the rules, not in response to end-user input. In direct contrast to the present invention, the entire purpose of RTA agents such as robots, artificial intelligences, and similar rule-based systems as described in *Wavish* is to minimize user interaction and control.

Summary of *Kanagawa*

Kanagawa teaches calculating the reliability, or mean time between failures (MTBF), of a group by letting a sample from the group run until failure. (*Kanagawa*, Abstract). *Kanagawa* then calculates whether the MTBF is acceptable or not using fuzzy logic sets. (*Kanagawa*, Abstract; *Kanagawa*, col. 2, ll. 10-16). The reliability demonstration test of *Kanagawa* does not use a failure prediction algorithm to predict failure, it lets devices run until they do fail, thereby demonstrating reliability. The reliability demonstration does not involve any prediction, and *Kanagawa* does not teach failure prediction. *Kanagawa* teaches the monitoring of failures in “fixed-time life tests,” which is fundamentally different than generating a failure prediction algorithm. (*Kanagawa*, col. 2, ll. 10-16).

The reliability demonstration test of *Kanagawa* does not use a failure prediction algorithm to predict failure, it lets devices run until they do fail, thereby demonstrating reliability. The reliability demonstration does not involve any prediction, and *Kanagawa* does not teach failure prediction. *Kanagawa* teaches the monitoring of failures in “fixed-time life tests,” which is fundamentally different than generating a failure prediction algorithm. (*Kanagawa*, col 2, ll. 10-16).

Applicants further respectfully submit that even if *Kanagawa*'s reliability demonstration were a failure prediction algorithm, it does not comprise fuzzy logic rules. *Kanagawa* does teach the use of fuzzy sets in deciding whether or not a lot has an acceptable MTBF. Fuzzy sets are fundamentally different than fuzzy logic rules, and their use in *Kanagawa* is also different than in Claim 25.

Fuzzy logic rules are logical expressions that operate on fuzzy sets (also known as fuzzy variables) to produce an output, much as an algebraic expression operates on a variable. See paragraphs [0052] and [0102]-[0118] of the Specification for a detailed description of fuzzy logic rules and fuzzy logic sets/variables. *Kanagawa* teaches the use of fuzzy logic sets in determining whether a group of devices is acceptable. Applicants submit, however, that *Kanagawa* does not teach fuzzy logic rules, and clearly does not teach a failure prediction algorithm that comprises fuzzy logic rules. *Kanagawa*'s fuzzy logic sets are not fuzzy logic rules, are not stored in a natural language format, and do not predict failure.

The Office Action also suggests that *Kanagawa* teaches the “gathering performance data for a storage system” of Claim 25 with “the ability to have ‘n items be drawn at random.’” (Office Action, pg. 7, ¶ 1; *Kanagawa*, col. 2, ll. 7-16). The *n* items of *Kanagawa* are a sample of a group or “lot.” (*Kanagawa*, col. 2, ll. 7-16). Selecting a random sample of items from a lot is clearly not gathering performance data for a storage system. *Kanagawa* does not teach a storage system, or gathering performance data for that storage system.

The Office Action further suggests that *Kanagawa* teaches “executing a failure prediction algorithm on the performance data to produce a result, the failure prediction algorithm comprising fuzzy logic rules. (Office Action, pg. 7, ¶ 1). As discussed above, *Kanagawa* lacks a failure prediction algorithm comprising fuzzy logic rules. Applicants further submit that *Kanagawa* does not teach **executing** a failure prediction algorithm on **performance data** to produce a **result**. Applicants respectfully submit that *Kanagawa* does not teach a failure prediction algorithm and further that *Kanagawa* does not teach executing anything.

The Office Action also suggests that *Kanagawa*'s teaching that “the coefficients a_{ij} must be chosen so that the membership functions are continuous” is equivalent to “tuning the failure prediction algorithm by adjusting a fuzzy variable definition” of Claim 25. (Office Action, pg. 7,

¶ 1). Applicants respectfully submit that defining a polynomial membership function as continuous is not equivalent to tuning a failure prediction algorithm by adjusting a fuzzy variable definition. *Kanagawa* is merely stating the fact that the membership functions (examples of which are illustrated in *Kanagawa*'s Table 1 on page 319) must be continuous. Even if this could be construed as a fuzzy variable definition, *Kanagawa* does not adjust the definition (it “**must**” be continuous), and clearly does not tune a failure prediction algorithm. At most, *Kanagawa* defines a membership function for an acceptability decision, but clearly does not tune a failure prediction algorithm by adjusting a fuzzy variable definition.

Summary of Cox

Cox provides a general description of how fuzzy logic may be used in control systems such as anti-lock braking systems and steam turbines. (*Cox*, pg. 58, col. 1, ¶ 4; *Cox*, pg. 59, col. 1, ¶ 2). *Cox* does not teach fuzzy logic rules comprising linguistic variables having less than four terms. In the example from *Cox* cited in the Office Action, the variable ‘temperature’ may have **at least six terms** “cold, cool, moderate, warm, hot, very hot,” **not less than four terms or three terms** as required by Claims 19 and 20. (Office Action, pg. 10, ¶ 3; *Cox*, pg. 58, col. 2, ¶ 2).

Summary of Vaneck

Vaneck describes a fuzzy controller used to chart paths for a small autonomous boat prototype vehicle using GPS. (*Vaneck*, Abstract; *Vaneck*, pg. 45, ¶ 3).

Summary of Andrade

Andrade teaches the use of parallel fuzzy processors in industrial process control. (*Andrade*, Abstract).

In view of the above described differences between the claimed invention and the art of record under the *Graham* analysis, Applicants respectfully submit that the claims at issue are not obvious. First, not all elements of the amended claims are taught or suggested in the art of record, and second, the art of record comes from vastly different fields than does the Applicants’

claimed invention and is clearly nonanalogous art. Applicants respectfully submit that *Bowles, Hughes, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade* do not teach assisting an end-user of a storage system in generating a failure prediction algorithm comprising fuzzy logic rules for the storage system, generating machine-readable code from the stored failure prediction algorithm, testing the machine-readable code with sample data to produce a result, or selectively revising the failure prediction algorithm such that the result corresponds to an expected result.

Applicants further submit that *Bowles, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade* are nonanalogous art. As quoted in M.P.E.P § 2143, the recent Supreme Court case of *KSR v. Teleflex* requires that, when determining “whether there was an apparent reason to combine the known elements in the fashion claimed by the patent at issue[,] to facilitate review, this analysis should be made explicit.” *KSR International Co. v. Teleflex Inc.*, 550 U.S. ___, ___, 82 USPQ2d 1385, 1396 (2007). Even if *Bowles, Hughes, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade* taught each and every element of the claimed invention, the Office Action has made no explicit analysis of why one of skill in the art of storage systems would look to the nonanalogous and disparate fields of the nuclear and aerospace industries, power systems, RTA autonomous agents, anti-lock braking systems, steam turbines, and small autonomous boats, or why such matter “logically would have commended itself to an inventor’s attention in considering his problem.” *In re Clay*, 966 F.2d 656, 659 (Fed. Cir. 1992).

Impermissible Hindsight

Appellants further respectfully submit that if the prior art of record so clearly demonstrates the obviousness of the claimed invention, a single reference would teach more than just one or two elements of the claimed invention. However, the formation of the combinations used in the rejections is indicative of impermissible hindsight analysis by the Examiner. The sheer number of references used from such extreme disparate fields of art seems to indicate that the claim terms were used in a key word search of the prior art, likely for the term “fuzzy logic.” For certain claims up to six different references are relied upon, and every rejection relies on at least four different references. Once a key word hit was found, there appears to be little analysis performed to determine the applicability of relevance of the reference. The present group of

prior art references is the third such group relied upon, and none of the groups teach each and every element of the claims, or relate remotely to storage devices. Appellants respectfully assert that because such analysis is improper the rejections should be overturned.

Given that *Bowles, Hughes, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade* fail to teach or suggest all of the elements recited in independent Claims 18, 25, 41, 47, 52, 56, and 62 and further given the other differences between the prior art and the claimed invention, Applicants respectfully submit that independent Claims 18, 25, 41, 47, 52, 56, and 62 are patentable over *Bowles, Hughes, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade*. Given that dependent Claims 19-21, 23-24, 27-29, 42-46, 48-51, 53-55, 57-61, and 63-66 depend from Claims 18, 25, 41, 47, 52, 56, and 62, Applicants respectfully submit that Claims 19-21, 23-24, 27-29, 42-46, 48-51, 53-55, 57-61, and 63-66 are also patentable over *Bowles, Hughes, Monsef, Wavish, Kanagawa, Cox, Vaneck, and Andrade*. Applicants respectfully request that the rejection of Claims 18-25 and 27-29 under 35 U.S.C. § 103(a) be withdrawn and that Claims 18-25, 27-29, and 41-66 be deemed allowable.

CONCLUSION

As a result of the presented remarks, Applicant asserts that Claims 18-21, 23-25, 27-29, and 41-66 are patentable and in condition for prompt allowance. Should additional information be required regarding the traversal of the rejections of the independent and dependent claims enumerated above, Applicants respectfully request that the Examiner notify Applicants of such need. If any impediments to the prompt allowance of the claims can be resolved by a telephone conversation, the Examiner is respectfully requested to contact the undersigned.

Respectfully submitted,

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